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Risk spillovers and diversification benefits between crude oil and agricultural commodity futures markets

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Abstract

This study examines the dependence structure and risk spillovers between crude oil and eight major agricultural futures (wheat, corn, soybean coffee, cotton, lumber, cocoa, and live cattle) markets. It also analyzes the potential conditional diversification benefits using a variety of copula functions and Conditional Value at Risk (CoVaR) measure. The results show significant crisis-sensitive and temporal dependence between oil and agricultural markets. Moreover, crude oil shows a symmetric tail dependence with both wheat, corn, soybeans, and cotton futures, whereas oil exhibits an average dependence with coffee. A strong dependence is observed between oil and cocoa (lumber) during bearish (bullish) market conditions. Oil and Live cattle have a symmetric dependence during bearish and bullish market conditions. On the other hand, we find asymmetric and bidirectional risk spillovers from oil to agricultural markets. Furthermore, the wheat futures contract appears to be the most dominating and vulnerable asset to oil price shocks, followed by lumber and corn futures, respectively, while the live cattle contracts are the least. Finally, an equally weighted portfolio offers the highest diversification benefits at a 5% expected shortfall.

JEL codes: G14

Keywords: commodity prices; spillovers; diversification benefits; copula.

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1. Introduction

Over the past decade, the global financial system has faced increased uncertainty, resulting in heightened volatility in both crude oil and agricultural commodity markets, with significant implications for financial system stability (Ziadat et al, 2023; Luo and Ji, 2018). The high volatility of crude oil prices can be attributed to various factors, including global demand and supply dynamics, financial crises, and geopolitical conflicts (Alomari et al., 2022; Kang et al., 2017; Mensi et al. 2023). As crude oil serves as a primary energy source for agricultural production (Jiang et al., 2022, Shahzad et al., 2018) rising oil prices impact agricultural commodity prices through higher production costs driven by increased energy requirements, affecting inputs such as fertilizer and transportation (Natanelov et al., 2011; Silvennoinen and Thorp, 2016; Yip et al., 2020). Therefore, there is a direct link between the energy sector and crop production costs due to the energy intensive nature of agriculture (Koirala et al, 2015; Reboredo, 2012), and this link further extends to impact the pricing of alternative oil substitutes, including biofuels such as Ethanol and Biodiesel, derived from agricultural outputs (Shahzad et al., 2018).

Between September 2003 and July 2008, crude oil prices experienced a significant surge, rising from less than $30 per barrel to reach a record high of approximately $147 (Ji et al., 2018; Sun and Shi, 2015). The prices of agricultural products exhibit similar fluctuation patterns to crude oil (Fowowe, 2016; Gong et al., 2023; Rezitis, 2015). For instance, the volatility in oil prices has had a cascading effect on crucial agricultural commodities, such as soybean, maize, and wheat, leading to a reversion of their prices to 2007 levels (Fasanya and Akinbowale, 2019; Nazlioglu and Soytas, 2011). Additionally, during the recent COVID-19 pandemic, commodity prices, including agricultural commodities, experienced notable increases. For instance, rice prices rose by 217%, wheat prices by 136%, corn prices by 125%, and soybean prices by 107% (El Montasser et al, 2023).

The main driving force behind this increase is the rising cost of oil substitutes, such as biofuels, is driving agricultural commodity prices higher (Dahl et al., 2020; Shahzad et al. 2018; Tiwari et al., 2022). Moreover, changes in biofuel prices can also affect fossil fuel prices by affecting demand through the substitution channel, which can lead to bidirectional volatility spillovers across markets, and a better understanding of these relationships can benefit consumers and producers in the long run (Han et al., 2020; Mensi et al., 2014). The substitution relationship between fossil fuels and biofuels is economically reasonable. For example, as a result of the substitution effect between fuel and bio-energy, an increase in biofuel production would exert downward pressure on high oil prices (Su et al., 2019). On the other hand, higher oil prices increase the demand for ethanol, a type of biofuel, leading to higher prices for agricultural products in a mechanism that accepts agricultural products as inputs to energy sources (Paris, 2018; Peñaranda and Micola, 2009). Therefore, producing biofuels to supplement conventional fuels could increase food prices and create sharp increases and volatility in the futures prices of corn, soybeans and crude oil (Chang and Su, 2010).

Notably, the US ethanol policy in 2005 (expanded in 2007 by the Energy Independence and Security Act to include more renewable fuel mixes), envisioning a preference for clean and lowcost ethanol over traditional hydrocarbons, has increased interest in examining the dynamics between energy and agricultural commodity markets. A serious of studies indicate that presence of unidirectional return/volatility spillovers from crude oil to agricultural commodity markets (e.g., Ji et al., 2018; Pal and Mitra, 2020; Zhang and Qu, 2015) while others find evidence that there is both unidirectional and bidirectional return/volatility spillovers from agricultural commodity markets to crude oil markets (e.g., Dahl et al., 2020; Du et al., 2011; Han et al., 2020; Kang et al., 2019; Nazlioglu et al., 2013; Naaem et al., 2022; Shahzad et al., 2018; Tiwari et al., 2022; Yip et al., 2020). This paper extends the understanding of linkages between crude oil and agricultural commodity markets.

Amidst the heightened interdependence of international equity markets brought about by the global financial crisis of 2007-2008, investors have been actively exploring alternative instruments to diversify their portfolios and mitigate equity risk (Rehman et al. 2023; Makkonen et al., 2021). While the increased volatility spillover between crude oil and agricultural markets complicates risk management for portfolio managers and agricultural producers (Yip et al., 2020), the historically low correlation between energy and agricultural commodities, along with conventional financial assets, has drawn the interest of investors seeking diversification opportunities (Pal and Mitra, 2019). This has led to the recognition of commodity futures as a distinct financial asset class, contributing to effective portfolio diversification (Rehman and Vo, 2020; Kang et al., 2017; Silvennoinen and Thorp, 2016). Particularly, agricultural commodity futures, as an early and crucial component of the futures market, provide a means to hedge or mitigate price risk, minimizing potential losses resulting from adverse price fluctuations (Dai et al., 2022; Liu et al., 2019; Makkonen et al., 2021).

A voluminous literature has considered the returns and/or volatility connectedness between agricultural commodity markets and crude oil (e.g., Dahl et al., 2020; Diebold and Yilmaz, 2017; Hung, 2021; Ji and Fan, 2012; Khalfaoui et al., 2023; Mensi et al., 2014; Nazlioglu et al., 2013; Shahzad et al., 2018; Sun et al., 2021; Tiwari et al., 2022). However, there is no study investigates the pricing dynamics of related markets in terms of tail dependency, risk spillovers and diversification benefits. Therefore, the main motivation of this paper is to fill the gap in the existing literature by examining tail dependency, risk spillovers and diversification benefits between crude oil and agricultural commodity futures markets. In doing so, this study enhances our understanding of the relationship between crude oil and agricultural commodity futures markets, uncovers asymmetric spillovers between these markets, and evaluates the potential diversification benefits of including agricultural commodity futures in an oil portfolio using a dynamic conditional diversification benefit approach.

This study makes significant contributions to the existing literature on three key aspects. Firstly, we explore the relationship between WTI crude oil and various agricultural commodity futures (such as wheat, corn, soybeans, coffee, cocoa, cotton, lumber, and live cattle) across different market conditions. Our analysis focuses on different types of copulas, namely the Normal copula, Student-t copula, Clayton copula, rotated Clayton copula, Gumbel copula, rotated Gumbel copula, and Symmetrized Joe-Clayton (SJC) copula. Each copula captures different aspects of dependence, including zero tail dependence, symmetric tail dependence, asymmetric tail dependence, and upper/lower tail dependence.

Secondly, we employ the CoVaR (Conditional Value at Risk) method, as introduced by Adrian and Brunnermeier (2016), to analyze risk spillovers. Unlike traditional Value at Risk (VaR), CoVaR captures asymmetric bidirectional spillovers (downside/upside) between markets, offering a more precise evaluation of risk in uncertain portfolios. CoVaR measures the maximum potential loss that an investor may experience within a specific time horizon and confidence level, considering both long and short positions. This approach is widely used to examine systemic risk and the transmission of failures across financial markets.

Thirdly, we investigate the potential diversification benefits of adding agricultural commodity futures to an oil portfolio using the conditional diversification benefit (CDB) method introduced by Christoffersen et al. (2012, 2017). This approach considers changing correlation and spillover patterns between oil and agricultural commodity futures, allowing us to examine non-linear dependence and higher-order moments, especially during extreme market events. The CDB measure overcomes the limitations of static models by providing time-varying optimal weights for diversification, thereby accurately estimating the underlying diversification benefits in different market conditions.

The next section provides related studies in current literature. Section 3 describes data and summarizes descriptive statistics. Section 4 introduces the econometric framework. Section 5 presents and discusses the results obtained from the study. Section 6 concludes the paper.

2. Related studies

Following the 2007-2008 global financial crisis (GFC), examining the transmission dynamics between crude oil and agricultural commodities has become a focus of interest for researchers. There is a significant number of studies using various datasets and econometric methods in this field, but the literature gives heterogeneous results. Given the extensive literature on the topic, we confine the literature to only those studies that focus on spillovers in commodity markets. Table 1 provides a brief overview of the main findings and methodologies used in previous studies.

Table 1: *Summary of previous studies*

Study	Data	Method	Commodity	Key findings
Wang et al. (2020)	2000-2019 Daily	MF-DCCA	WTI crude oil, wheat, copper, gold	The study identifies multifractality cross-correlations between crude oil and all agricultural futures, both before and after COVID 19.
Jiang et al. (2022)	2004-2022 Monthly	TVGCT test DY (2012,2014) spillover index	WTI crude oil futures, agricultural futures index, and three Chinese agricultural futures	The findings unveil unidirectional causality and asymmetric, bidirectional volatility spillovers, particularly during financial crises and natural disasters.
Kang et al. (2017)	2002-2016 Daily	DECO-GARCH DY(2012)	WTI crude oil, wheat, rice, corn, silver, gold	The study shows that an increased positive connections, bidirectional spillovers, and gold/silver transmitting information, while other commodities receive information during crises.
Živkov et al. (2020)	2006-2019 Daily	Component GARCH Quantile regression Modified ICSS algorithm	Brent crude oil, corn, wheat, soybean, and canola.	Their findings indicate that the short-term impact of the oil market has a slightly stronger influence on agricultural commodities compared to its long-term effect.

Pal and Mitra (2020)	2005-2018 Daily	Baruník and Křehlík (2018)	crude oil, wheat, corn, soybean, ethanol	The study indicates that crude oil has a stronger spillover effect on ethanol, corn, soybeans, and wheat during energy and food crises.
Mensi et a. (2014)	2000-2013 Daily	VAR-BEKK-GARCH VAR-DCC-GARCH	WTI oil, Europe Brent oil, gasoline, heating oil, barley, corn, sorghum, and wheat	The study uncovers notable spillover effects between energy (WTI oil, European Brent oil, gasoline, and heating oil) and cereal (barley, corn, sorghum, and wheat) commodity markets.
Nazlioğlu et al. (2013)	1986-2011 Daily	CI V IR F	Oil, corn, sugar, wh soybe	The study find that there is no transmission of risk between oil and agricultural markets before the crisis, but volatility spillovers to agricultural commodity markets excluding sugar in the post-crisis period.
Kang et al. (2019)	1990-2017 Monthly	Baruník and Křehlík (2018)	cereals, dairy, meat, sugar, vegetable oils	Vegetable oils were identified as the primary drivers of price and volatility in both markets, while also revealing bi-directional and asymmetric connectedness across various frequency bands between the two markets.
Hung (2021)	2018-2020 Daily	DY (12) and wavelet coherence model	crude oil, wheat, sugar, soybean, corn, oats, copper	The study indicates a heightened return spillover between crude oil prices and agricultural commodity markets during the COVID-19 crisis compared to the pre-COVID outbreak period.
Dahl et al. (2020)	1986-2016 Daily	DY (09,12,14,15) spillover index	crude oil and ten major agricultural commodities	The study identifies an asymmetric and bidirectional spillover relationship between crude oil and agricultural commodities, particularly during periods of financial and economic turmoil.
Mensi et a. (2021)	1997-2018 Daily	Baruník and Křehlík (2018), and wavelet method	28 commodity futures markets	The study reveals that an increased intensity of spillover connections among precious metals, industrial metals, energy, agriculture, and livestock in the face of economic and political events.
Umar et (2021)	2002-2020	Granger cau DY	11 agricultural commodities	The study shows that the level of connectedness increases during financial crisis periods.

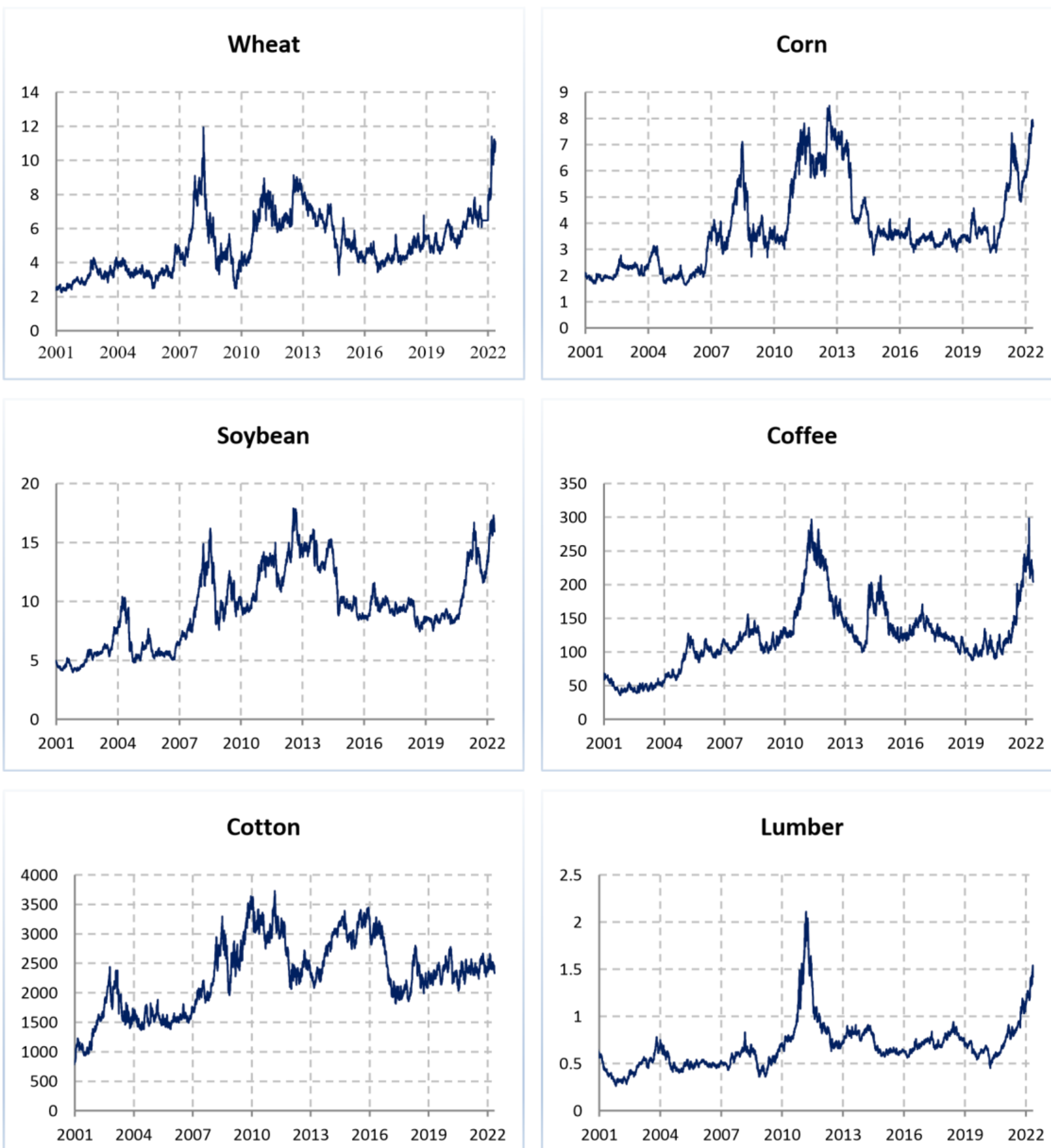
				The energy sector plays a key role in causing significant impacts on other areas, and there are close connections among energy, industrial metals, and precious metals.
Diebold and Yilmaz (2017)	19 commodities	2006-2016 Daily	Variance decompositions spillover index	The study finds that agricultural futures are less connected during normal periods, serving as diversifiers, but become more
Iqbal et al. (2023)	9 commodity futures	2008-2020 5 -min	Quantile VAR, RTD	connected during the COVID-19 crisis, while energy futures, especially light crude oil and heating oil, exhibit higher connectedness, and metal futures, including gold, show increased volatility connections during the COVID-19 era.

Notes. Causality in variance (CIV), Impulse response functions (IRF), Diebold and Yilmaz (2009, 2012, 2014, 2015) DY (09, 12, 14, 15), Relative tail dependence (RTD).

Another strand of research that models the dependence between crude oil and agricultural commodities using copula functions has gained significant momentum in recent years. To accurately managing portfolio risk, it is necessary to measure investor dependencies and tails (Rehman et al., 2022). Copula analysis improves the capture of tail dependencies by accounting for deviations from normality in extreme market conditions, providing a more comprehensive approach (Rehman et al., 2023; Ji et al., 2018; Supper et al., 2020). Reboredo (2012), for example, finds weak dependence between world oil and maize, soybean and wheat prices. Koirala et al. (2015) emphasize that a strong positive correlation between energy futures prices and agricultural commodity futures prices. Mensi, Tiwari et al. (2017) report that time-varying asymmetric tail dependence between the pairs of cereals and between oil and cereals across short-term, mediumterm, and long-term investment horizons. Mensi, Hammoudeh et al. (2017) examine the dependence structure and risk spillovers between crude oil prices and major regional developed stock markets and find that there is a tail dependence between crude oil prices and all stock markets for the raw return series. Jiang et al. (2018) conclude that agricultural raw material markets lead the global oil market, which, in turn, leads metal markets, the dependence structure varies over time, and the financial crisis has a notable impact on the interdependencies among these markets. Yahya et al. (2019) show that the connectedness between oil and agricultural products has increased post-2006 across all frequencies, particularly for longer investment horizons. Mokni and Youssef (2019) reveal that a stronger immediate impact of crude oil prices on agricultural commodity prices compared to delayed effects. Kumar et al. (2021) conclude that a strong correlation between oil market crashes and declines in agricultural commodities during crisis periods.

3. Data and summary statistics

Our dataset, spanning from January 1, 2000 to May 5, 2022, includes daily closing prices of oil and eight agricultural futures, i.e. WTI crude oil and cocoa, coffee, corn, cotton, live cattle, lumber, soybean, and wheat. We extracted it from DataStream terminal. The daily return series are calculated as logarithmic first difference of indices and we plot the price and return dynamics of futures in Figures 1 and 2, respectively. We observe that futures prices, see Figure 1, follow different trend before 2013 and a sudden peak observed around 2007 or 2010, coinciding with the 2007-2009 global financial crisis and Eurozone debt crisis, characterizes futures series. In addition, the effect of health crisis in 2020 on evolution of prices becomes evident for all but cotton futures; U.S. oil futures contract prices had dropped in negative territory and back in positive territory soon after while the agricultural assets, except for cocoa, marked a sharp surge with the onset of the COVID-19 pandemic. Evidence of volatility clustering and fat tails in return series, plotted in Figure **2**, prompt the use of nonparametric models.



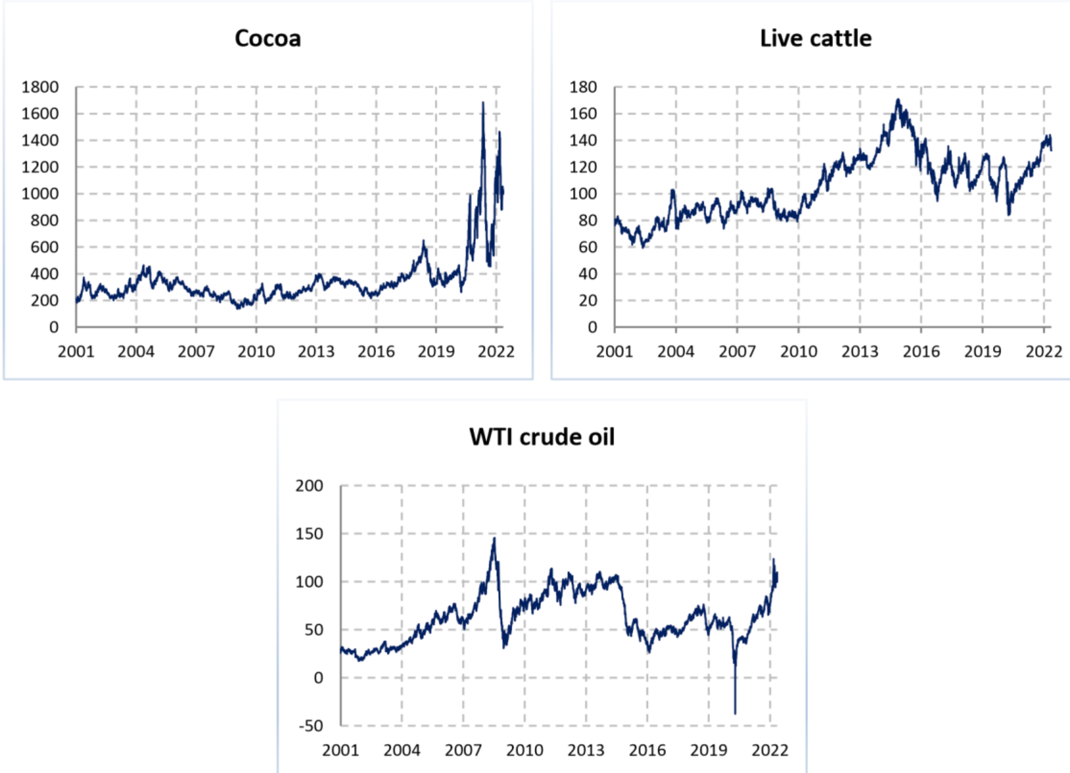
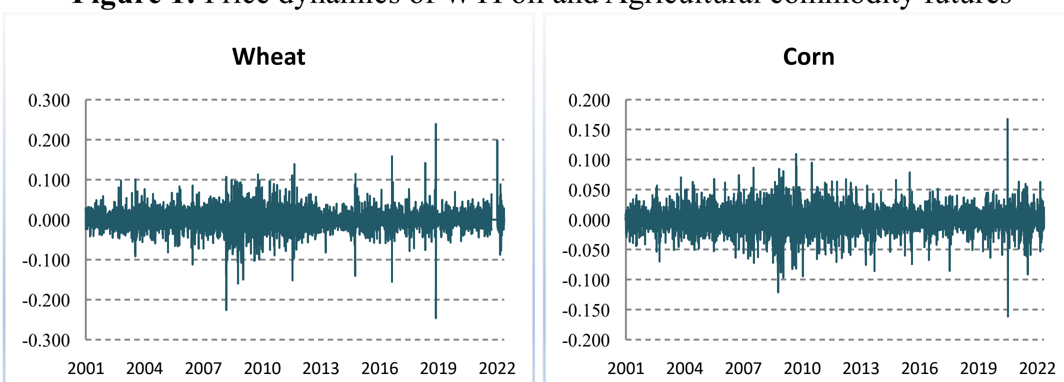


Figure 1: Price dynamics of WTI oil and Agricultural commodity futures



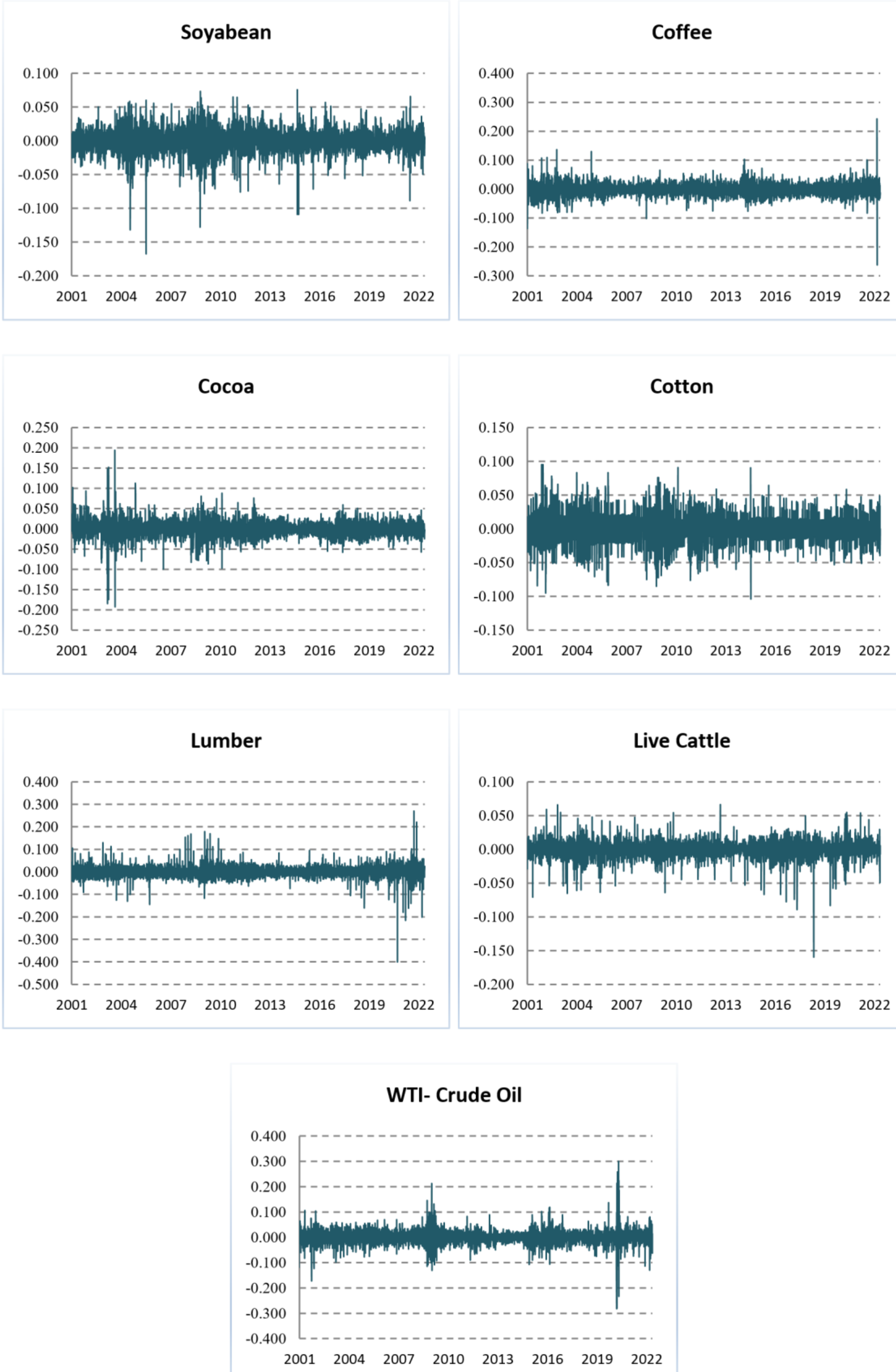


Figure 2: *Return dynamics of WTI oil and Agricultural commodity futures*

Table 2: *Summary statistics of commodity futures price returns*

	Wheat	Corn	Soya beans	Coffee	Cocoa	Cotton	Lumber	Live cattle	WTI
Mean	0.0002	0.0002	0.0002	0.0001	0.0001	0.0001	0.0002	0.0001	0.0004
Maximum	0.2391	0.1680	0.0757	0.3154	0.1938	0.0953	0.2696	0.0664	0.3002
Minimum	-0.2467	-0.1619	-0.1674	-0.2626	-0.1928	-0.1040	-0.4006	-0.1595	-0.2822
Std. Dev.	0.0241	0.0185	0.0156	0.0210	0.0176	0.0195	0.0246	0.0112	0.0266
Skewness	-0.0728	-0.1372	-0.7279	0.4651	-0.1842	0.0096	-0.4205	-1.1385	0.2926
Kurtosis	9.3260	4.9377	6.9595	20.6006	13.3852	1.8276	21.7742	13.3416	16.5329
JB	21771.4***	6121.55***	12652.5***	106411.0***	44869.1***	836.7572***	118816.0***	45840.4***	68484.8***
Correlation	0.1346***	0.1721***	0.1824***	0.0903***	0.0446***	0.1631***	0.0545***	0.0581***	-
ADF	-18.8217***	-16.2502***	-17.2142***	-19.4443***	-19.2537***	-17.7918***	-16.4279***	-18.4695***	-16.1425***
PP	-6335.49***	-6120.46***	-6476.01***	-5683.37***	-6249.95***	-6266.45***	-5417.42***	-5527.04***	-5979.94***
ARCH [20]	870.791***	847.237***	816.335***	598.043***	777.239***	1118.60***	86.211***	143.397***	5716.41***
Q [20]	78.972***	43.051***	38.202***	38.442***	37.780***	37.455**	93.282***	66.263***	71.072***

Notes: ***, ** and * represent significance level at 1%, 5% and 10%, respectively.

We delineate the descriptive statistics of each return series in Table 2. Results reveal that all futures contracts post a positive average return, closes to zero during the sample period. As indicated by standard deviations, the crude oil market is more volatile than agricultural commodity markets. The lumber has the highest volatility, whereas the live cattle contract has the lowest volatility among agricultural futures. Coffee, cotton, and WTI have a right-skewed distribution, while the remaining variables exhibit negative skewness. All futures returns are leptokurtic given positive extreme kurtosis values. Neither agricultural nor oil futures contract follow a normal distribution, as suggested by the JB statistics. Oil market is positively and moderately correlates with all agricultural market contracts, with the strongest and least correlations coefficients for soybeans and cocoa, respectively. Both market returns become stationary given the rejection of null hypothesis of ADF and PP tests at the 1% significance level. The results of ARCH and Ljung–Box tests provide evidence of ARCH and serial correlations effects up to 20 lags in all return cases.

4. Empirical methodology

3.1 Time varying copulas

To detect the presence of average and extreme tail dependence between oil and agriculture commodities, we use bivariate copulas. These copulas[2] are based on Sklar's theorem, which states that the joint distribution function i.e. $F_{XY}(x, y)$ for two continuous random variables X and Y can be expressed in the form of copula functions $C(u, v)$ and the marginal distribution function of F_X and F_Y acting as random variables.

$$F_{XY}(x, y) = C(u, v) \tag{1}$$

Above equation comprises of $u = F_X(x)$ and $v = F_Y(y)$ which highlights copula as a multivariate function with uniform marginal representing dependence between two random variables. This function is based on $RanF_x * RanF_y$ under continuous margins. We can also use copulas in connecting marginal to multivariate distribution function and later decompose into its respective copula to measure dependence along with its univariate marginal distributions. We can extract joint probability density of the variables X and Y using copula density $c(u, v) = \frac{\partial^2 C(u,v)}{\partial u \partial v}$ as highlighted below.

$$f_{XY}(x, y) = c(u, v) f_Y(y) f_X(x) \tag{2}$$

[2] Cherubini et al. (2004) introduce copulas. Readers are also referred towards Joe (1997) and Nelson (2006) for understanding copulas.

Equation (2) presents $f_Y(y)$ and $f_X(x)$ as marginal densities of variables Y and X, respectively. Therefore, in order to explain joint densities of the two random variables, information about marginal densities and the copulas is crucial. Another feature of copula is that it contains information about the probability of variables experiencing not only average but joint extreme upward or downward (tail) movement. We illustrate equations for upper (right) and lower (left) tail dependence extracted from the copulas as follows.

$$\lambda_U = lim_{u\to 1} Pr[X \geq F_X^{-1}(u) | Y \geq F_Y^{-1}(u)] = lim_{u\to 1} \frac{1 - 2u + C(u,u)}{1-u} \tag{3}$$

$$\lambda_L = lim_{u\to 0} Pr[X \leq F_X^{-1}(u) | Y \leq F_Y^{-1}(u)] = lim_{u\to 0} \frac{C(u,u)}{u} \tag{4}$$

In Equation (3) and (4), $\lambda_U, \lambda_L \in [0,1]$. The lower (upper) tail dependence suggests a non-zero probability for an extreme (small) large value on first series along with the extreme small (large) value for the second series.

In this paper, we use wide range of copulas with different dependence structures under time varying parameters. This combination comprises of symmetric as well as asymmetric copulas. Among symmetric copulas, these include bivariate Frank copula, Plackett copula with tail independence (or zero tail dependence), Student-*t* copula with equal lower and upper tail dependence and the Normal copula. The class of asymmetric copula includes Gumbel copula with upper tail dependence and lower tail independence, Symmetrized Joe Clayton with a special case of symmetric tail dependence, rotated Gumbel copula with upper tail independence and lower tail dependence and Clayton copula having upper tail independence and lower tail dependence. Time varying dependence for all the above-mentioned copulas is estimated by allowing dependence parameters to vary across time according to an evolution equation. For student *t* and Gaussian copula, we specify linear dependence parameter ρ_t, which develops following an ARMA $(1,q)$ process[3] as follows.

$$\rho_t = \wedge \left(\psi_0 + \psi_1 \rho_{t-1} + \psi_2 \frac{1}{q} \sum_{j=1}^{q} \left(\emptyset^{-1}(\mu_{t-j})\right) \left(\emptyset^{-1}(v_{t-j})\right)\right) \tag{5}$$

In Equation (5), $\wedge(x) = (1+e^{-x})(1-e^{-x})^{-1}$ presents a modified logistic transformation for keeping ρ_t in (-1,1). The dependence parameters in Equation (5) are presented through ψ_0, ψ_1 and ψ_2 denoting a constant, an autoregressive term and an average of the product over the last q observations of the transformed variables, respectively. For student-*t* copula, the parameter dynamics are presented again in Equation (5) however $\emptyset^{-1}(x)$ is replaced by $t_v^{-1}(x)$. Similar to

[3] For more information, see Patton (2006)

Gaussian and Student-*t* copula, dynamics of Gumbel and rotated Gumbel copulas follow an ARMA $(1, q)$ as per the following specification.

$$\delta_t = \omega + \beta\delta_{t-1} + \alpha\frac{1}{q}\sum_{j=1}^{q}\left|u_{t-j} - v_{t-j}\right| \tag{6}$$

The specification for the tail dependence of Symmetrized Joe Clayton (SJC) copula is as follows.

$$\lambda_t^u = \Delta\left(\omega_u + \beta_u\rho_{t-1} + \alpha_u\frac{1}{q}\sum_{j=1}^{q}\left|u_{t-j} - v_{t-j}\right|\right) \tag{7}$$

$$\lambda_t^L = \Delta\left(\omega_L + \beta_L\rho_{t-1} + \alpha_L\frac{1}{q}\sum_{j=1}^{q}\left|u_{t-j} - v_{t-j}\right|\right) \tag{8}$$

In Equations (7) and (8), $\Delta x = (1 + e^{-x})^{-1}$ which presents logistic transformation for keeping λ_t^u and λ_t^L in the range $(-1,1)$.

3.2 Value at risk and conditional value at risk

We quantify risk spillover between oil and agricultural commodity futures contracts utilizing upside and downside value at risk (VaR) and conditional value at risk (CoVaR) based on copula estimates. The VaR quantifies maximum amount of loss that an investor may experience for a specific period and confidence interval by getting into a long (downside) or a short (upside) position. We highlight expression for downside VaR at period *t* under the confidence interval $1 - \alpha$ as $r(r_t \leq VaR_{\alpha,t}) = \alpha$, estimated using marginal models as $VaR_{\alpha,t} = \mu_t + t_{\upsilon,\eta}^{-1}(\alpha)\sigma_t$. The terms μ_t and σ_t represent conditional mean and standard deviation, respectively derived from the dependence model (i.e. ARFIMA-GARCH in our case). Similarly, we present expression of upside VaR using $Pr(r_t \geq VaR_{1-\alpha,t}) = \alpha$ which results in $VaR_{1-\alpha,t} = \mu_t + t_{\upsilon,\eta}^{-1}(1-\alpha)\sigma_t$. Both equations consists of $t_{\upsilon,\eta}^{-1}(\alpha)$ which highlights αth quantile of the student *t* distribution.

To measure risk spillover from oil market to agricultural commodities, we use CoVaR measure proposed by Adrian and Brunnermeier (2011) which was later generalized by Girardi and Ergün (2013). The CoVaR measure is capable to highlight risk spillover as it increases with the transmission of failure between the associated markets (see Bisias et al. 2012). In our study, the CoVaR of agricultural commodzities (oil) present the sensitivity of the VaR of agricultural commodity(oil) market due to extreme movements in the oil (agricultural commodity) market(s). Suppose r^a and r^o as returns on agricultural and oil market, then the resulting downside CoVaR for agricultural market is appended as follows.

$$Pr\left(r_t^a \leq CoVaR_{\beta,t}^a \middle| r_t^o \leq VaR_{\alpha,t}^o\right) = \beta \tag{9}$$

In Equation (9), $VaR^{o}_{\alpha,t}$ provides α *th* quantile distribution of the oil returns with $\Pr\left(r^{o}_{t} \leq VaR^{o}_{\alpha,t}\right) = \alpha$ measuring maximum amount of loss that the oil market may undergo for any specific period under the confidence interval of $1-\alpha$. Similarly, the upside CoVaR for agricultural market results due to extreme upward returns movements in oil market can be specified as

$$Pr\left(r^{a}_{t} \geq CoVaR^{a}_{\beta,t} \middle| r^{o}_{t} \geq VaR^{o}_{1-\alpha,t}\right) = \beta \tag{10}$$

In the above equation, $VaR^{o}_{1-\alpha,t}$ measures maximum amount of loss by considering a short position for a period under the confidence interval of $1-\alpha$. To present CoVaR in equations (9)-(10) in terms of copulas, the resulting conditional probabilities are as follows.

$$C\left(F_{r^{a}_{t}}\left(CoVaR^{a}_{\beta,t}\right), F_{r^{o}_{t}}\left(VaR^{o}_{\alpha,t}\right)\right) = \alpha\beta \tag{11}$$

$$\begin{aligned} 1 - F_{r^{a}_{t}}\left(CoVaR^{a}_{\beta,t}\right) - F_{r^{o}_{t}}\left(VaR^{o}_{1-\alpha,t}\right) + C\left(F_{r^{a}_{t}}\left(CoVaR^{a}_{\beta,t}\right), F_{r^{o}_{t}}\left(VaR^{o}_{1-\alpha,t}\right)\right) \\ = (1-\alpha)(1-\beta) \end{aligned} \tag{12}$$

The expressions $F_{r^{o}_{t}}$ and $F_{r^{a}_{t}}$ highlight marginal distribution for oil and agricultural returns, respectively. According to Reboredo and Ugolini (2015), two steps are involved in the estimation of CoVaR. First step involves solving equation (11) or (12) to get value of $F_{r^{m}_{t}}\left(CoVaR^{m}_{\beta,t}\right)$ for copula function and the significance level of VaR and CoVaR i.e. α and β, respectively. Second step computes CoVaR as ${F_{r^{m}_{t}}}^{-1}\left(F_{r^{m}_{t}}\left(CoVaR^{m}_{\beta,t}\right)\right)$ with the help of distribution function for agricultural commodities using ARFIMA-FIGARCH marginal model. Furthermore, to add robustness to our results, we apply K-S test proposed by Abadie (2002) for measuring systemic risk comparison between VaR ($\mathrm{VaR}^{\beta,t}_{a}$) and the CoVaR ($\mathrm{CoVaR}^{\beta,t}_{a}$) for both agricultural and oil markets. The application of K-S test enables us to measure difference between two quantile functions based on the empirical distribution function, however, does not rely on any underlying distribution function (Li and Wei, 2018).

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} \sup_{x} \left|F_{m}(x) - G_{n}(x)\right| \tag{13}$$

$\mathrm{G_n(x)}$ and $\mathrm{F_m(x)}$ in the above equation denotes distribution functions for VaR and CoVaR, respectively whereas *n* and *m* highlight size of the two samples.

The null hypothesis of no systemic impact between oil and agricultural commodities and the alternative hypothesis can be described below:

$$H_0: CoVaR_{\beta,t}^{a} = VaR_{\beta,t}^{a} \tag{14}$$

$$H_1: CoVaR_{\beta,t}^{a} < VaR_{\beta,t}^{a} \tag{15}$$

3.3 Conditional diversification benefits (CDB)

Christoffersen et al. (2012) and Christoffersen and Simutin (2017) proposed a test statistic to measure diversification benefits of assets in a portfolio. This test, commonly known as conditional diversification benefit, uses expected shortfall measure to quantify diversification benefits under probability *q* and at time *t* as follows.

$$CDB_t(\omega_{t,}q) = \frac{\omega_{t,}ES_{i,t}(q) + (1-\omega_t)ES_{g,t}(q) - ES_{p,t}\left(\omega_{t,}q\right)}{\omega_{t,}ES_{i,t}(q) + (1-\omega_t)ES_{g,t}(q) - VaR_t\,(q)} \tag{16}$$

In the above equation, ω_t represent weight of the financial asset *i* at time *t* in portfolio *p* whereas *ES* denotes expected shortfall.

$$ES_{z,t}(q) = -E\left[r_{z,t} | \, r_{z,t} \leq F_{z,t}^{-1}(q)\right] \tag{17}$$

In the above equation, *z = i, g* where $F_{z,t}^{-1}(q)$ represents an inverse distribution function for asset *z* at time *t*, $\omega_t ES_{i,t}(q) + (1-\omega_t)ES_{g,t}(q)$ represents an upper bound for the portfolio's expected shortfall, $ES_{p,t}(\omega_{t,}q)$. The $VaR_t(q)$ = - $F_{p,t}^{-1}(q)$ gives information about value at risk (VaR) in a portfolio provided by the *qth* quantile of lower bound of expected shortfall. For this reason, the CDB measure provides value in the range [0,1]. The increasing value of CDB implies greater diversification benefits in a portfolio however such diversification benefits depend on the asset's composition and the probability *q* of the portfolio. For such reasons, we measure CDB under different combinations of assets weight in a portfolio under a passive trading strategy. The weights are kept constant over time at 5% and 50% corresponding to lower tail and median distribution of returns. The equation for expected shortfall for our multivariate marginal distribution function under Student *t* distribution is as follows.

$$ES_{z,t}(q) = -\mu_{z,t} + \frac{\sigma_{z,t}}{q}\, h\big(H^{-1}\,(q)\big)\left[\frac{\upsilon + H^{-1}\,(q^2)}{\upsilon - 1}\right] \tag{18}$$

Above equation consists of *H* and *h* which highlights cumulative distribution function and standard Student density with *υ* degrees of freedom, respectively for which the associated VaR is appended below.

$$VaR_t\,(q) = -\mu_{p,t} - \sigma_{p,t}H^{-1}\,(\alpha) \tag{19}$$

5. Empirical results

5.1. Dependence analysis

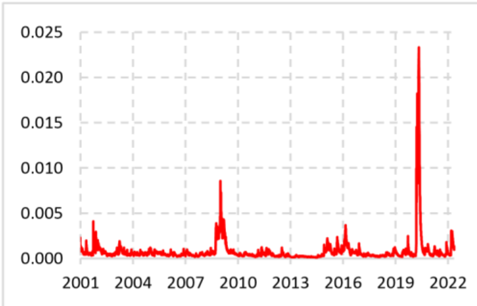
A preliminary and essential step for the estimation of dependence between oil and agricultural futures return is to define the marginal model and we present the results in Table 3. It should be noted that the results are based on an ARFIMA-FIGARCH model with skewed student-t distributions since it allows long memory in futures returns without violating normality assumption, where the optimal values of p, q, r and m parameters are defined by minimizing the ACI (p=0,1,2 considered). The findings in Panel A demonstrate evidence in favor of persistence in mean for wheat, corn, and live cattle futures contracts, pointing out the existence of long-range dependence in returns and therefore rendering them predictable. We also find that the AR(1) parameter in the conditional mean equation is statistically significant only for wheat, corn, and live cattle, indicating that past information is rapidly impounding into their current futures prices. Looking at the results from the conditional volatility equation in Panel B, we observe that volatility is quite persistent for the most of returns—wheat, corn, soybeans, coffee, cotton, lumber, and live cattle—as indicated by statistically significant GARCH[Beta1] parameter. Such result shows the volatility in agricultural markets depends not only on past volatility, but also on concurrent shocks to returns. In addition, the estimated fractional differencing parameter d (d-FIGARCH) is statistically significant for both market futures returns, indicating the presence of high degree of persistence in volatility, with crude oil futures being the most persistent, followed by wheat, soybeans, and corn, and cocoa being the least persistent among variables. Asymmetric volatility (leverage) effects are quite evident in most of futures, i.e., wheat, soybeans, coffee, cotton, lumber, live cattle, and WTI contracts. The statistically significant coefficients of the tail parameter reveals evidence of leptokurtic behavior for both markets, indicating that agricultural and oil markets significantly deviate downside or upside from current price levels. With the exception of soybeans and coffee, diagnostic test findings in Panel C demonstrate no ARCH effects in residuals in all cases. In addition, we find evidence against the presence of serial correlation in all but lumber cases in the residuals (Q[20]) and other than soybeans, coffee, and cocoa in the squared residuals (Q2[20]) of marginal distribution models. Overall, the results suggest no misspecification errors in marginal models for oil and agricultural futures returns.

Table 3: *Estimate results of marginal model*

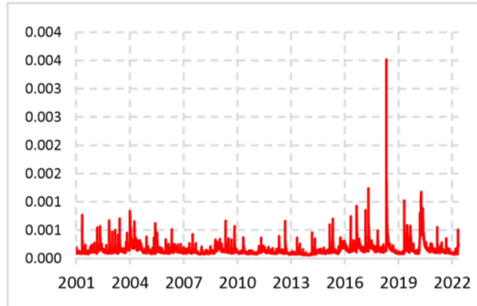
	Wheat	Corn	Soybeans	Coffee	Cocoa	Cotton	Lumber	Live cattle	WTI
Panel A: Mean Equation									
Cst[M]	0.0003	0.0004	0.0006***	-0.0000	0.0003*	0.0002	-0.0004	0.0006***	0.0010***
	(0.0001)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
d-Arfima	-0.0973**	0.0737*	0.0352	0	0.0236	0.0069	0.0205	0.0858***	0.0324
	(0.0404	(0.0431)	(0.0221)	(0.022)	(0.0176)	(0.0289)	(0.0163)	(0.0211)	(0.0315)
AR[1]	0.6312***	0.5076***	0.0656	-0.1639	-0.1221	0.218	-0.176	0.8655***	0.3064
	(0.1195)	(0.0988)	(0.2829)	(0.4669)	(0.3879)	(0.1392)	(0.1408)	(0.023)	(0.1898)
MA[1]	-0.5662***	-0.5982***	0.0022	0.2119	0.0861	-0.3131**	0.2390**	-0.9101***	-0.3691*
	(0.1139)	(0.1198)	(0.3011)	(0.4468)	(0.3988)	(0.1545)	(0.1334)	(0.015)	(0.204)
Panel B: Variance Equation									
Cst[V]	-0.5662***	0.1324***	0.0662***	0.3217**	0.6758	0.1505***	0.2009***	0.1308**	0.0656
	(0.1139)	(0.05)	(0.0238)	(0.1324)	(0.4387)	(0.0563)	(0.0559)	(0.0583)	(0.0502)
d-Figarch	0.4881***	0.4277***	0.4627***	0.2633***	0.2055***	0.3723***	0.2737***	0.3381***	0.8674***
	(0.1228)	(0.0744)	(0.0885)	(0.0472)	(0.0498)	(0.0534)	(0.0295)	(0.0834)	(0.2521)
ARCH[Phil1]	0.3349***	0.3099***	0.3131***	0.4283***	0.1393	0.3922	0.6264***	0.4146***	0.1259
	(0.0715)	(0.0564)	(0.0416)	(0.0999)	(0.3194)	(0.0559)	(0.0643)	(0.1266)	(0.1629)
GARCH[Beta1]	0.7023***	0.6506***	0.7184***	0.6120***	0.2984	0.6841***	0.7686***	0.6202***	0.8849
	(0.0826)	(0.0872)	(0.0692)	(0.1125)	(0.3533)	(0.0717)	(0.0496)	(0.1441)	(0.0968)
Asymmetry	1.4897***	-0.0205	-0.4480***	0.4028***	0.0241	0.0866***	0.1846***	-1.2431***	-0.3541***
Tail	31.467***	3.1867***	4.2492***	5.4378***	5.8651***	4.3866***	8.5650***	14.340***	2.6976***
Panel C: Diagnostics tests									

LL	14351.4	15643.9	16756.9	15308.4	16151.1	15124.9	14305.3	18829.2	14156.4
AIC	-4.9185	-5.3618	-5.7435	-5.2467	-5.5357	-5.1838	-4.9027	-6.4541	-4.8516
ARCH[20]	0.1047	1.0672	1.7844	1.6686	1.5552	0.9178	0.7371	0.5626	1.0665
	[1.0000]	[0.3775]	[0.0170]	[0.0310]	[0.0543]	[0.5640]	[0.7908]	[0.9392]	[0.3783]
Q[20]	20.3533	27.7038	12.1496	24.5521	15.079	11.5929	30.1618	28.8291	12.4423
	[0.3133]	[0.0667]	[0.8394]	[0.1377]	[0.6565]	[0.8675]	[0.0359]	[0.0505]	[0.8236]
Q2[20]	2.0468	22.5434	36.1602	32.4909	32.7032	18.4309	14.441	9.7474	21.7972
	[0.9999]	[0.2087]	[0.0067]	[0.0192]	[0.0181]	[0.4276]	[0.6999]	[0.9398]	[0.2411]

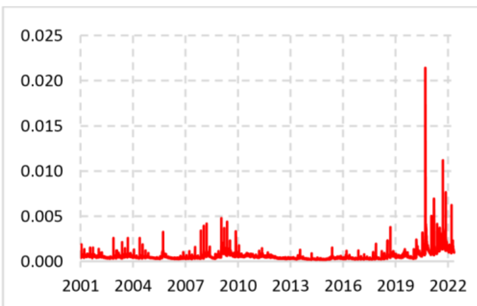
Notes: The above table presents estimates of maximum likelihood along with the standard deviations of parameters under marginal distribution of the model. We use combination of different values between “0” and “2” for selecting the p, q, r and m lag values. LL is the Log-likelihood values of marginal distribution models while Q[20] and Q2[20] denote empirical Ljung Box statistics as autocorrelation of commodities returns and squared return series. ARCH [20] highlights autoregressive conditional heteroscedasticity. ***, ** and * indicates the rejection of the null hypothesis at a 1%, 5% and 10% significance level, respectively.



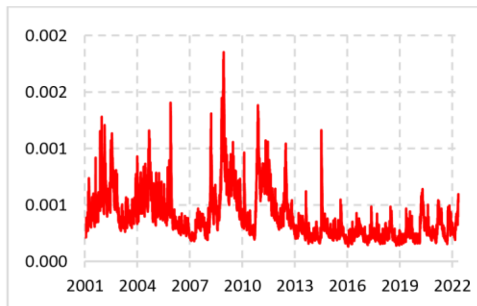
a) Wheat



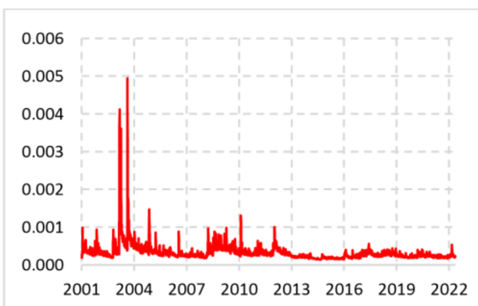
b) Corn



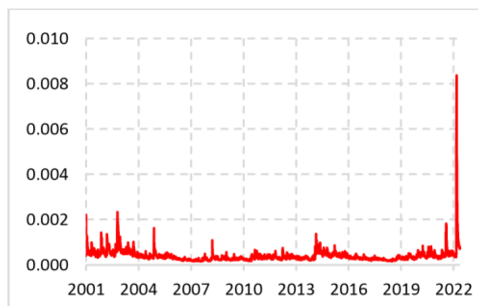
c) Soybeans



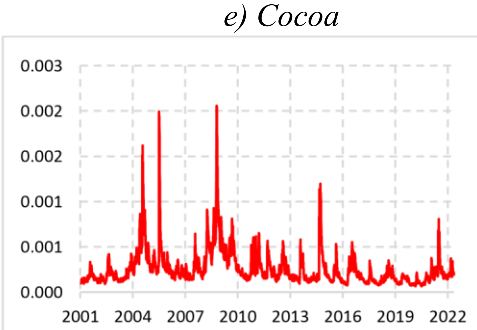
d) Coffee



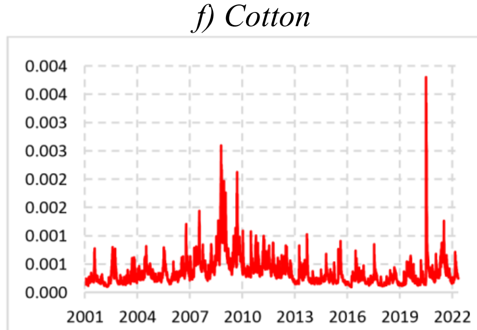
e) Cocoa



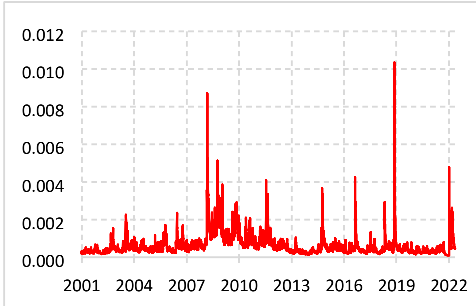
f) Cotton



g) Lumber



h) Live cattle



i) Oil

Figure 3: *Volatility estimates of commodity futures.*

In the next step, we calculate time-varying copulas between oil and agricultural futures markets. Parameter estimates to model the dependence structure through seven copula functions are given in Table 4. The best-fitted copula model for each asset pair, including the crude oil and one agricultural futures contract, are determined by minimizing AIC value as was the case in Wen et al. (2017), Reboredo (2018), Mensi et al. (2021), etc. The results, reported in Table 4, demonstrate that the Symmetrized JC copula emerges as the best fit for wheat, corn, soybeans, and cotton futures, whereas the Gaussian copula is the best fit for coffee; the Clayton copula for cocoa; the Rotated Gumbel for lumber, and the Student-t copula for live cattle. Our result differs from Mensi et al. (2017), who discover no tail dependence for undecomposed series of oil-wheat and oil-corn pairs but find evidence of asymmetric tail dependence for oil-corn pair in the long-term. More precisely, four out of eight markets are featured concurrently by the existence of lower and upper (symmetric) tail dependence (see Panel F), while the coffee market is described as the symmetric no-tail dependence (see Panel A). Likewise, the lower tail dependence but upper tail independence emerges for cocoa and lumber, whereas the live cattle market exhibits symmetric—with equal lower and upper—tail dependence. Although both the cocoa and lumber futures contracts co-move with oil market during bearish market circumstances, the results suggest a decoupling pattern when markets are bullish. The time varying SJC copula estimates for wheat, soybeans, and cotton reveal that all parameters β_U, β_L, α_U, α_L are statistically and significantly negative. These findings imply the presence of a high level (β_U and β_L) and time-variant persistence (α_U and α_L) in the dependence. Likewise, the conditional upper tail dependence $\dot{\omega}_U$ and conditional lower tail dependence $\dot{\omega}_L$ for wheat and cotton significantly negative but positive for soybeans. The results show a higher possibility of joint extreme events during both bearish and bullish circumstances for these markets. Conversely, the time-varying estimated parameters (Ψ_1 and Ψ_2) for Clayton and Student-t copulas appear to be statistically significant for cocoa and live cattle and this result confirms that the dependence between oil markets with cocoa and live cattle varies in time. This result confirms Wen et al. (2017), who find a dynamic dependence and thus time-variant diversification benefits between energy stocks and commodity futures.

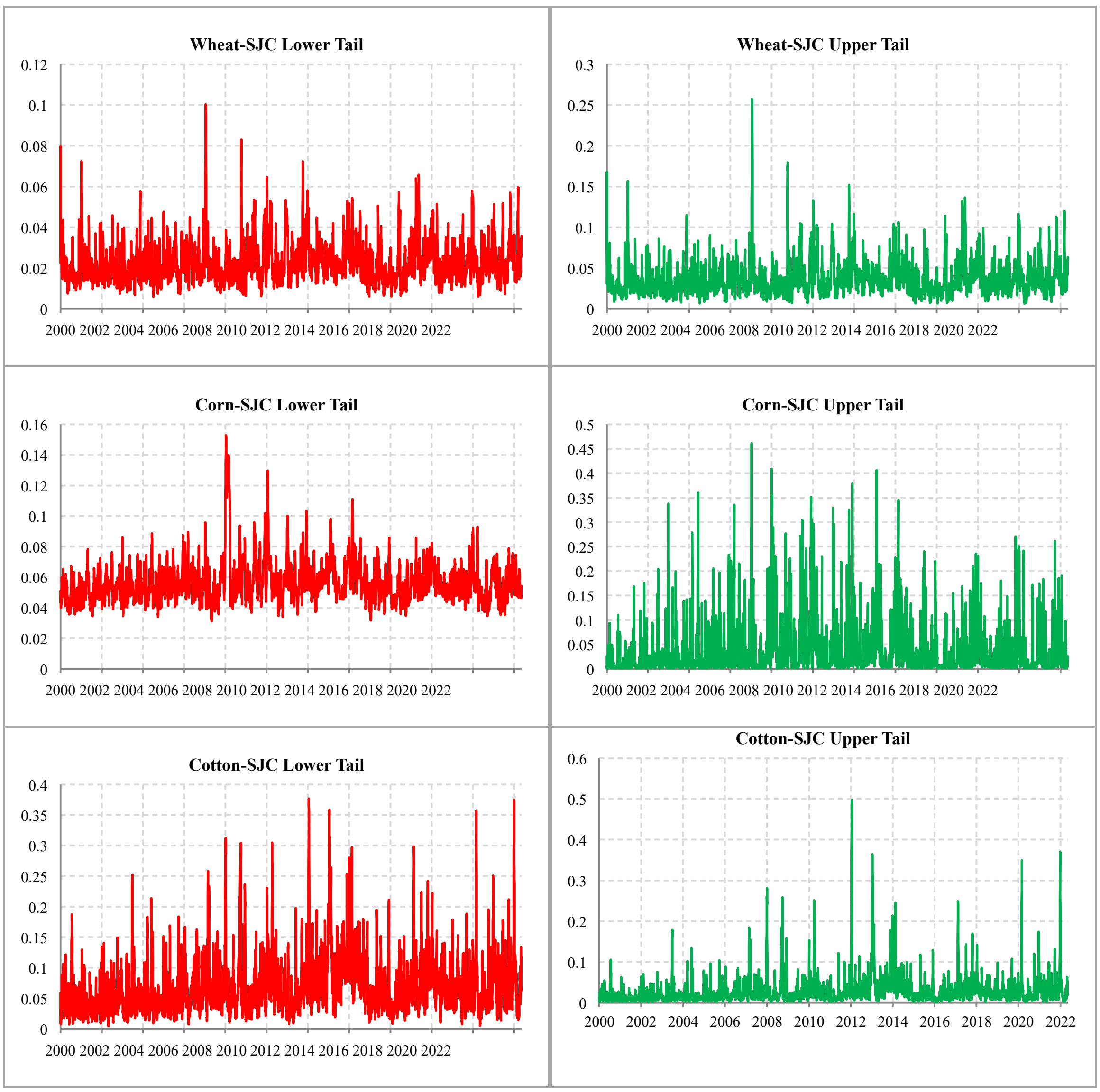
Table 4: *Results of time varying copulas between WTI oil and agricultural commodity futures returns*

	Wheat	Corn	Soybeans	Coffee	Cocoa	Cotton	Lumber	Live cattle
Panel A: Gaussian Copula (no tail dependence, tail independence)								
ω	-0.0004***	-0.0019***	0.6229***	0.0007***	0.0014***	0.5379***	0.1752***	0.2415***
	(0.0005)	(0.0005)	(0.0777)	(0.0004)	(0.0010)	(0.0804)	(0.0619)	(0.0533)
α	0.0092***	0.0089***	0.2448***	0.0121***	0.0107***	0.1754***	0.1950***	0.1492***
	(0.0029)	(0.0025)	(0.0722)	(0.0036)	(0.0046)	(0.0702)	(0.0770)	(0.0575)
β	2.0112***	2.0255***	-1.5624***	1.9996***	1.9724***	-1.5047***	-1.2185***	-1.9805***
	(0.0071)	(0.0045)	(0.2988)	(0.0057)	(0.0204)	(0.3973)	(0.8124)	(0.0697)
AIC	-153.981	-210.28	-239.888	**-133.562**	-29.482	-172.095	-32.697	-33.467
Panel B: Clayton Copula (lower tail dependence)								
Ψ_0	0.2738***	0.7747***	1.0317***	0.8769***	0.7381***	0.4128***	0.7826***	0.2463***
	(0.0558)	(0.1520)	(0.1179)	(0.0389)	(0.0290)	(0.0686)	(0.0260)	(1.0900)
Ψ_1	0.9987***	-0.8141***	-0.6151***	-0.4751***	0.3372***	0.6954***	-0.8855***	1.1313
	(0.1388)	(0.4211)	(0.1959)	(0.0878)	(0.0345)	(0.0870)	(0.1310)	(17.3400)
Ψ_2	-0.1205***	-0.5877***	-1.4132***	-1.3344***	-1.6439***	-0.3676***	-1.2869***	-0.1423
	(0.1222)	(0.3864)	(0.3355)	(0.1130)	(0.0568)	(0.1778)	(0.0509)	(15.1837)
AIC	-107.068	-165.614	-217.335	-105.856	**-45.053**	-179.078	-41.642	-51.416
Panel C: Rotated Clayton Copula (upper tail dependence)								
ω	0.3435***	0.3951***	1.1239***	0.3744**	0.5155***	0.7098***	0.4881***	0.8018***
	(2.2398)	(0.0218)	(0.0813)	(44177.2)	(0.0651)	(0.1688)	(0.1397)	(0.1046)
α	0.8397***	0.7644***	-0.8779***	0.826	0.6007***	-0.5246***	0.5145***	-1.1763***
	(5.5204)	(0.0426)	(0.1536)	(16317.4)	(1.3893)	(0.5269)	(0.5150)	(0.1524)
β	-0.2543***	-0.3884***	-1.6563***	-0.4115***	-1.1442***	-0.6425***	-0.8515***	-1.7914***
	(1.6657)	(0.0286)	(0.3165)	(7419.30)	(0.7190)	(0.3644)	(0.1495)	(0.2293)
AIC	-117.689	-154.423	-183.57	-83.135	-12.817	-130.011	-30.15	-22.063
Panel D: Gumbel Copula (upper tail dependence)								
ω_u	-1.0651***	-0.5769	1.8081***	-0.7524***	-0.2432***	-0.6272***	-0.6019***	0.0341
	(136.8242)	(10.8581)	(0.3264)	(27.9327)	(0.3346)	(0.1464)	(0.1521)	(2.4357)
α_u	1.2799***	0.9156	-0.9705***	1.0474***	0.6993***	0.9333***	0.9629***	0.2287***
	(116.1672)	(0.3875)	(0.2790)	(53.1095)	(0.2430)	(0.1021)	(0.1013)	(2.2852)
β_u	-0.0992	-0.3838	-1.2270***	-0.3232***	-1.1006***	-0.2645***	-0.6641***	-0.1686***
	(13.7639)	(71.2054)	(0.2723)	(7.6773)	(0.3422)	(0.1151)	(0.1753)	(0.2175)
AIC	-140.819	-180.108	-220.765	-103.483	-20.125	-173.158	-46.462	-47.485
Panel E: Rotated Gumbel Copula (lower tail dependence)								
ω_L	-1.0707***	-0.7073***	1.6701***	-0.6490***	-0.0127**	-0.6096***	0.5114***	-1.1894***
	(0.2011)	(0.6962)	(0.2974)	(0.0052)	(0.3913)	(0.1150)	(2.3554)	(11.4022)
α_L	1.2846***	1.0018***	-0.8614***	0.9730***	0.5304	0.9198***	-0.0304	1.3937***
	(0.1627)	(0.4358)	(0.2511)	(0.0015)	(0.3015)	(0.0793)	(2.0342)	(9.7239)

β_L	-0.1000***	-0.2517***	-1.1351***	-0.3860***	-1.1493	-0.2640***	-0.8154	-0.1453**
	(0.0841)	(0.9409)	(0.2241)	(0.0421)	(0.3280)	(0.0948)	(0.7462)	(5.2767)
AIC	-134.341	-193.49	-249.907	-123.834	-44.885	-211.553	**-54.467**	-72.157
Panel F: Symmetrized Joe-Clayton Copula (asymmetric tail dependence, upper and lower tail dependence)								
$\dot{\omega}_U$	-1.9607***	3.0752	2.1672***	-1.8850***	-17.6777***	-0.6338***	-16.4722	-17.9473**
	(1.0875)	(0.0000)	(1.6400)	(2.5125)	(169.4849)	(1.4907)	(59.8665)	(592.9723)
β_U	-5.7111***	-24.9990***	-18.7030***	-11.1784***	-0.7289	-12.2094***	-2.4543	-1.6729
	(3.7725)	(0.0000)	(8.5105)	(8.2149)	(57.5066)	(7.5179)	(30.3869)	(161.1151)
α_U	6.3283***	-4.8725	-6.0066***	-3.3676***	0.0168	3.8596***	-0.0118***	-0.0049
	(3.6769)	(0.0000)	(3.2444)	(33.6485)	(1.6359)	(2.2254)	(1.0019)	(1.1288)
$\dot{\omega}_L$	-2.8264***	-3.0959	0.4443***	0.0657***	0.0168***	-0.7068***	2.2315	-0.5886
	(1.7852)	(0.0000)	(1.0399)	(1.2709)	(1.1759)	(1.3991)	(2.2012)	(1.5337)
β_L	-4.4374***	-1.2736	-9.0260***	-11.6438***	-24.9999***	-7.7976***	-24.9926	-13.49
	(5.8212)	(0.0000)	(3.9458)	(4.0734)	(5.2122)	(4.5663)	(11.0955)	(7.0381)
α_L	11.1837***	10.9586	-6.4895***	-0.6151***	-3.8245***	2.4789***	-6.9475	4.4664
	(12.6654)	(0.0000)	(4.2766)	(5.5010)	(1.9079)	(3.5243)	(6.6655)	(2.8559)
AIC	**-156.763**	**-222.129**	**-273.329**	-119.793	-35.328	**-224.655**	-42.666	-62.292
Panel G: Student-t Copula (symmetric tail dependence)								
Ψ_0	-0.0002***	-0.0017***	-0.0013***	0.0007***	0.1980***	-0.0020***	0.0709***	0.0322***
	(0.0005)	(0.0008)	(0.0051)	(0.0003)	(0.0634)	(0.0016)	(0.0541)	(0.0637)
Ψ_1	0.0063***	0.0048***	0.0056***	0.0067***	0.0570***	0.0036***	0.0394***	0.0164***
	(0.0023)	(0.0019)	(0.0188)	(0.0025)	(0.0589)	(0.0027)	(0.0287)	(0.0243)
Ψ_2	2.0074***	2.0229***	2.0228***	2.0026***	-1.7510***	2.0266***	0.7884***	1.4898***
	(0.0078)	(0.0086)	(0.0401)	(0.0050)	(0.5269)	(0.0155)	(0.8667)	(0.9973)
υ	5.0000***	4.9954***	4.9947***	5.0000***	5.0000***	4.9926***	5.0000***	5.0000***
	(0.2856)	(0.2465)	(0.2497)	(0.2745)	(0.3352)	(0.2345)	(0.2450)	(0.3300)
AIC	-130.447	-135.59	-216.789	-95.346	65.169	-204.407	-23.024	**-133.599**

Notes: ***, ** and * indicates the rejection of the null hypothesis at a 1%, 5% and 10% significance level, respectively. The minimum AIC value (in bold), adjusted for small-sample bias, indicates the best fit for copulas and q parameter for the time-varying framework is "8". Values in the first row represent parameter estimates for each copula model and values in the second row and parenthesis are standard errors. U and L stands for upper and lower tail dependence, respectively.

Figure 4 demonstrates the evolving dependence structure under the best-fit copula specifications given in Table 4 and it provides deeper insights into time-varying tail dependence between agricultural commodity futures and oil markets. A visual inspection suggests the level of tail dependence is not constant but time-varying throughout the sample period, intensifying during the major events, such as the 2007-2009 financial crisis; the 2010-2012 Eurozone sovereign debt crisis; the 2014 oil prices shock, and the COVID-19 period, supporting Yahya et al. (2019), who show the financial and economic crisis periods considerably affect the oil-agricultural nexus. The two copula specifications that produce the best fit are the Symmetrized JC copula with three and the Rotated Gumbel with two pairs of agricultural commodities. More precisely, the results provide evidence of symmetric tail dependence for live cattle futures (student-t copula); asymmetric tail dependence for wheat, corn, and cotton futures (Symmetrized JC copula), and zero tail dependence for coffee futures (Gaussian copula) with oil markets. We may infer from zero dependence on coffee futures that it provides a safe-haven property for investors in the oil market during a downturn, where the effect is more prominent during the global financial crisis. The strengthening of lower dependence demonstrates that cotton investors suffer the largest losses, followed by live cattle, corn and wheat futures during difficult times. Conversely, the Clayton and Rotated Gumbel copulas show lower tail dependence but upper tail independence for soybean, cocoa, and lumber futures with the oil markets, indicating that oil market returns co-move in extreme negative returns but decouple from the respective futures during bullish market conditions. This suggests a higher loss potential during a downturn and a lower profit diversification potential when markets are bullish for soybean, cocoa, and lumber futures investors combined with the oil market.



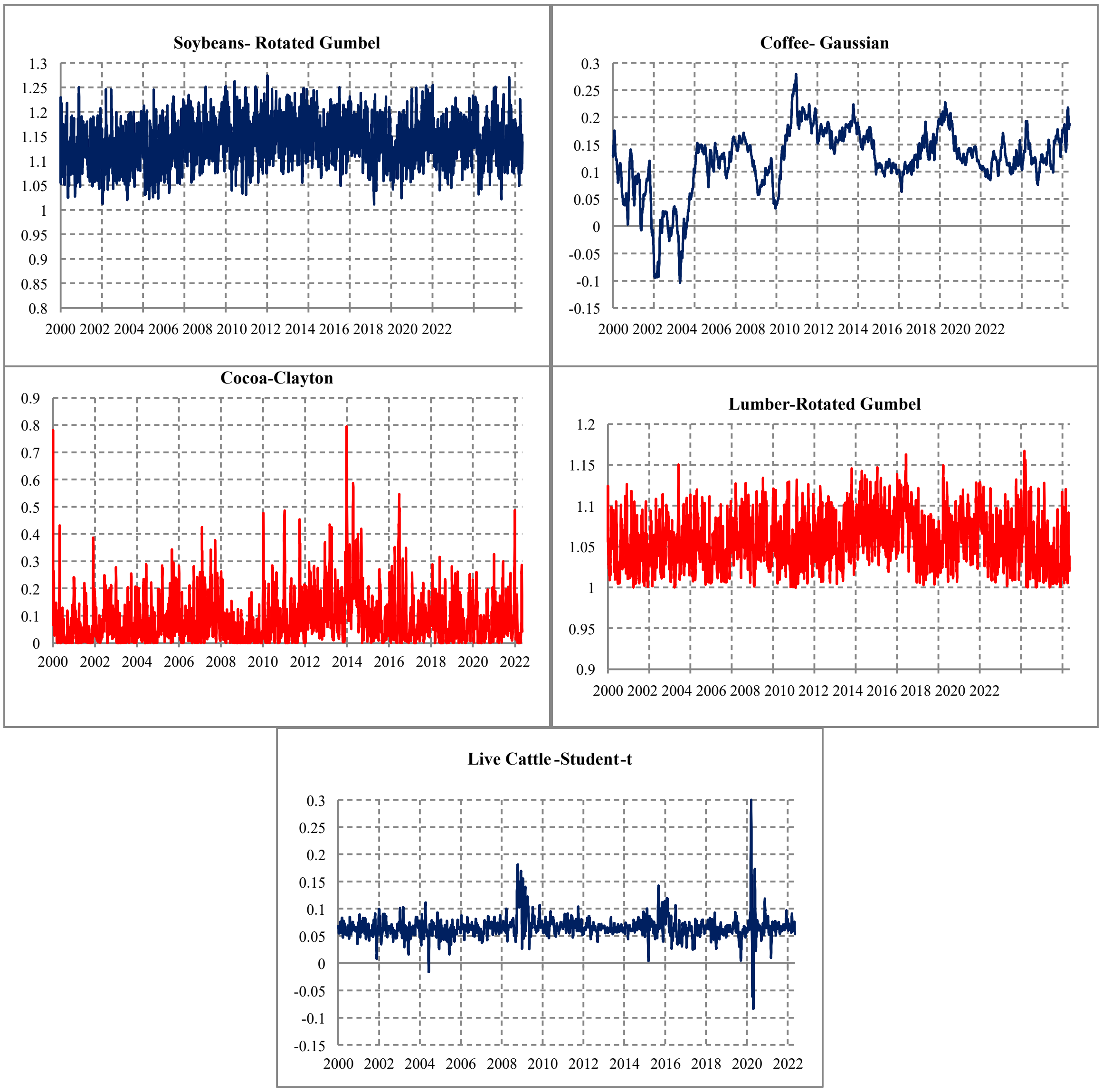


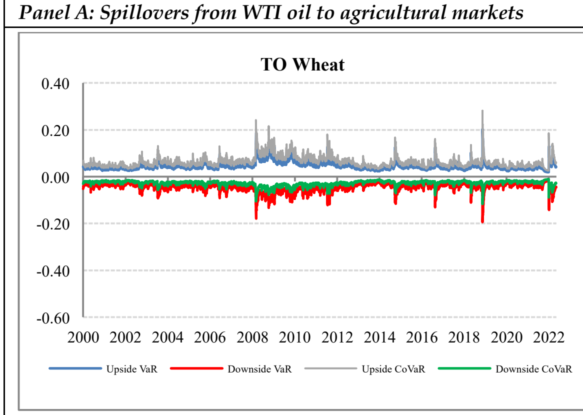
Figure 4: *Temporal dependence between WTI oil and agricultural commodities.*

5.2. Risk spillovers analysis

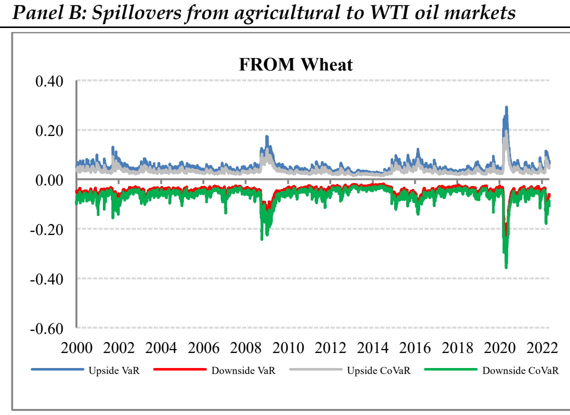
The calculation of the conditional VaR (CoVaR) enables us to evaluate the impact of upside and downside price spillovers on the agricultural futures markets from the crude oil market and vice versa. To do so, the temporal dynamics of the downside and upside CoVaR and VaR estimates for 0.05 and 0.95 values for both α and β, are calculated and given in Figure 5. As indicated by Reboredo (2018), the price spillover effects, determined by the dependence structure between the oil and agricultural markets, emerge in the case of deviations in CoVaR from VaR values. The wider the departure, the stronger the spillover risk effect that occurs between two markets. We should note that the red and green solid lines indicate the downside VaR and CoVaR of agricultural or oil market futures, while the blue and gray solid lines reflect the upside VaR and CoVaR of the same.

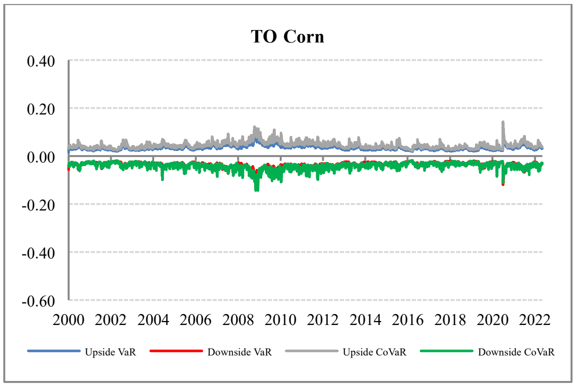
It is obvious that the extent of spillover effects varies over time for each futures contract and in both directions, with dramatic increases following or during large event occurrences (Reboredo, 2018; Ji et al., 2018; Mensi et al., 2021). The results in Panels A and B indicate that in virtually all situations, downside and upside VaR, as well as conditional VaR values, follow similar upward and downward trends, with minor differences in magnitude in two directions, indicating limited evidence of price spillovers for all but soybeans and cocoa futures with the crude oil market. The visual inspection shows relatively low co-movements between oil and agricultural futures and therefore underscore the presence of tail diversification effects for one market against extreme price fluctuations in other market. Regarding spillovers from the agricultural markets, unconditional downside VaR values for agricultural markets mostly and systematically larger than CoVaR values, and this is true for the unconditional upside VaR compared to CoVaR values, thus reinforcing the findings from Ji et al. (2018). As for spillovers from oil market, however, the results in Panel A suggest that unconditional VaR values are larger than that of CoVaR values for the downward spillovers from the oil market, whereas the opposite is true for the upward spillovers, confirming Meng et al. (2020) for a comparable finding between crude oil and Chinese commodity futures. Overall, the limited evidence of price spillovers and low co-movement between the oil and agricultural markets, driven by a narrower gap between the CoVaR and VaR, have implications for investors in both markets, as they may benefit from the hedging capabilities of oil or agricultural futures during periods of extreme market movements.

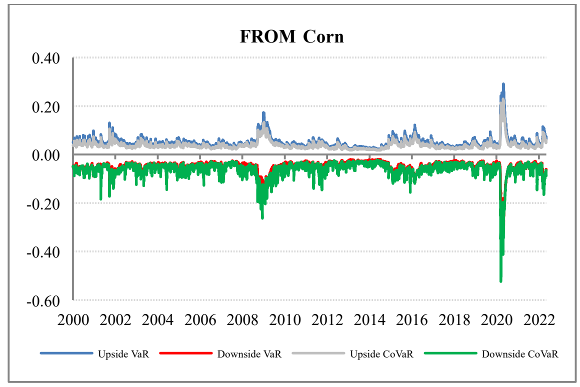
Panel A: Spillovers from WTI oil to agricultural markets



Panel B: Spillovers from agricultural to WTI oil markets




TO Corn
0.40
0.20
0.00
-0.20
-0.40
-0.60
2000 2002 2004 2006 2008 2010 2012 2014 2016 2018 2020 2022
Upside VaR
Downside VaR
Upside CoVaR
Downside CoVaR


FROM Corn
0.40
0.20
0.00
-0.20
-0.40
-0.60
2000 2002 2004 2006 2008 2010 2012 2014 2016 2018 2020 2022
Upside VaR
Downside VaR
Upside CoVaR
Downside CoVaR


TO Soybeans
FROM Soybeans
TO Coffee
FROM Coffee
TO Cocoa
FROM Cocoa
TO Cotton
FROM Cotton
0.40
0.20
0.00
-0.20
-0.40
-0.60
2000 2002 2004 2006 2008 2010 2012 2014 2016 2018 2020 2022
Upside VaR
Downside VaR
Upside CoVaR
Downside CoVaR

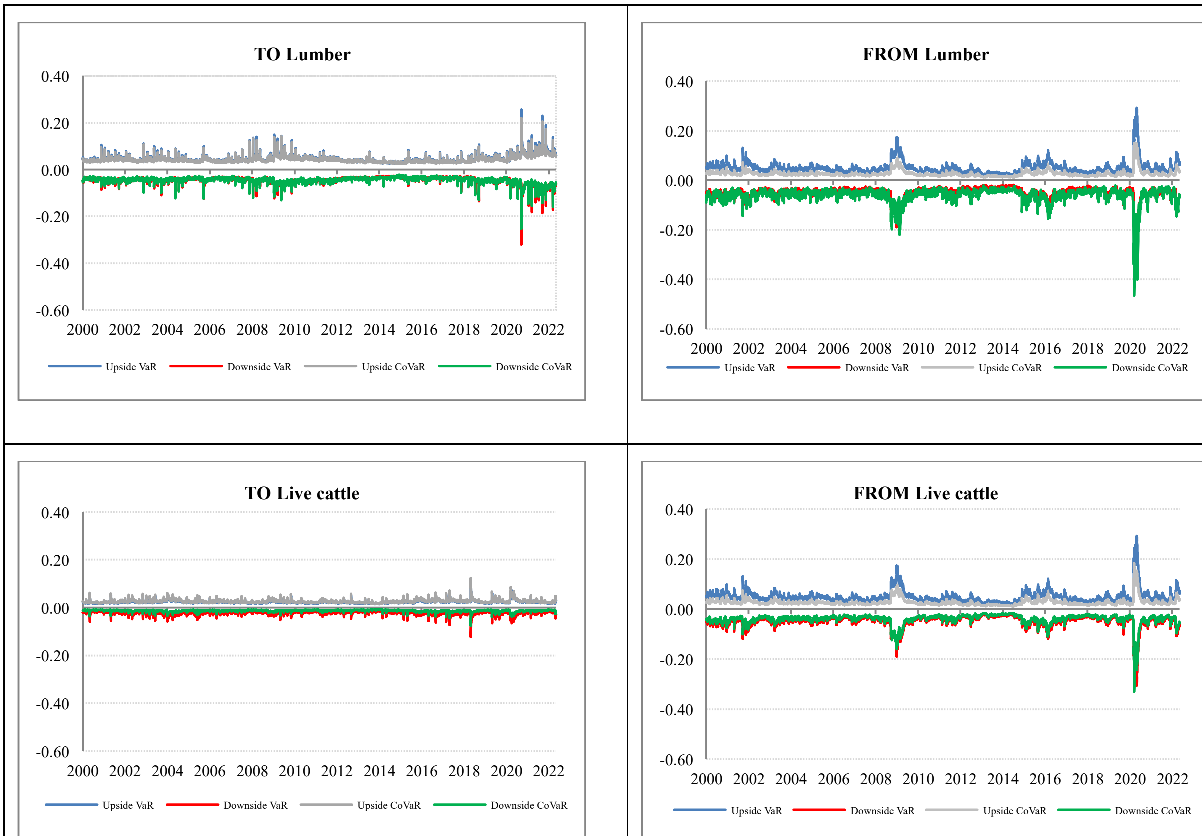


Figure 5*:* Time-varying downside and upside price spillovers between WTI oil and agricultural futures markets

Table 5 provides the average upside and downside VaR and CoVaR values for both cases, where the relatively small average values confirms the results depicted in Figure 5. In addition, the average downside and upside VaR values from WTI to agricultural futures range from -0.0453 to 0.0450, but they remain constant for all agricultural futures in the opposite direction for downside and upside risks, with an average of 0.0488 and -0.0471, respectively. The difference between the CoVaR and VaR values suggests a higher spillover effect from agricultural futures to the oil market rather than the other way around, and wheat appears to be by far the most sensitive asset to the upside and downside shocks emanating from the oil market, whereas both downside and upside soybeans risk shocks are the most influential asset on oil market than other agricultural commodities, supporting Ji et al. (2018) for their wheat and soybeans commodities with oil and gas markets.

Table 5: *Static upside and downside spillovers between oil and agricultural futures*

	Upside VaR	Downside VaR	Upside CoVaR	Downside CoVaR
Panel A: Spillovers from WTI oil to agricultural markets				

Wheat	0.0450	-0.0453	0.0617	-0.0273
	(0.0169)	(0.0169)	(0.0231)	(0.0102)
Corn	0.0359	-0.0352	0.0449	-0.0400
	(0.0107)	(0.0107)	(0.0134)	(0.0140)
Soybeans	0.0301	-0.0291	0.0206	-0.0551
	(0.0095)	(0.0096)	(0.0064)	(0.0180)
Coffee	0.0376	-0.0376	0.0421	-0.0277
	(0.0100)	(0.0100)	(0.0104)	(0.0069)
Cocoa	0.0347	-0.0340	0.0291	-0.0339
	(0.0085)	(0.0085)	(0.0070)	(0.0087)
Cotton	0.0378	-0.0373	0.0518	-0.0398
	(0.0094)	(0.0093)	(0.0129)	(0.0101)
Lumber	0.0439	-0.0445	0.0415	-0.0444
	(0.0146)	(0.0145)	(0.0132)	(0.0131)
Live cattle	0.0234	-0.0226	0.0258	-0.0130
	(0.0062)	(0.0063)	(0.0070)	(0.0037)
Panel B: Spillovers from agricultural to WTI oil markets				
Wheat	0.0488	-0.0471	0.0340	-0.0629
	(0.0251)	(0.0254)	(0.0168)	(0.0319)
Corn	0.0488	-0.0471	0.0386	-0.0594
	(0.0251)	(0.0254)	(0.0195)	(0.0334)
Soybeans	0.0488	-0.0471	0.0287	-0.0869
	(0.0251)	(0.0254)	(0.0140)	(0.0423)
Coffee	0.0488	-0.0471	0.0292	-0.0458
	(0.0251)	(0.0254)	(0.0163)	(0.0287)
Cocoa	0.0488	-0.0471	0.0250	-0.0484
	(0.0251)	(0.0254)	(0.0124)	(0.0247)
Cotton	0.0488	-0.0471	0.0388	-0.0584
	(0.0251)	(0.0254)	(0.0186)	(0.0298)
Lumber	0.0488	-0.0471	0.0262	-0.0592
	(0.0251)	(0.0254)	(0.0129)	(0.0304)
Live cattle	0.0488	-0.0471	0.0269	-0.0398
	(0.0251)	(0.0254)	(0.0141)	(0.0230)

Note: The table presents the average VaR and the corresponding CoVaR values. The p-values are presented in brackets.

Afterwards, we utilize the K-S test considering three different tests to find out whether the impact of spillovers under VaR and CoVaR specifications changes or not and report the test statistics alongside with the probability values given in square brackets in Table 6. Given the reported pvalues in the first and second columns are lower than any conventional significance level, we can strongly reject the null hypothesis of equality and thus confirm the existence of statistically difference between unconditional downside/up VaR and conditional downside/up VaR (CoVaR) for both markets and conclude that investors react differently to upside and downside trends. This result confirms those of Kumar et al. (2021), who show the evidence of inequality between the downside/upside VaRs and their respective the downside/upside CoVaR values for all commodity returns and argue that rising uncertainty in oil market will negatively affect the commodity returns. Similarly, the results of Test 3, shown in the third column, show an asymmetry of upside and downside risk spillovers between oil and agricultural markets, indicating that the extent of the upside risk spillover is significantly greater than the downside risk spillover for all agricultural commodity futures. This suggests disentangling downside and upside risks to avoid losses when taking risk and portfolio management decisions. Our findings are partly in line with Shahzad et al. (2018) for the existence of significant and strong asymmetry of upside and downside risk spillovers between oil and agricultural markets, including soybeans and wheat.

Table 6*: Tests of equalities and asymmetries of upside and downside VaR-CoVaR*

	Testing Downside Risk Spillover	Testing Upside Risk Spillover	Testing the asymmetry of upside and downside risk
	$H_0: CoVaR_D = VaR_D$	$H_0: CoVaR_U = VaR_U$	$H_0: \frac{CoVaR_D}{VaR_D} = \frac{CoVaR_U}{VaR_U}$
	$H_1: CoVaR_D \neq VaR_D$	$H_1: CoVaR_U \neq VaR_U$	$H_1: \frac{CoVaR_D}{VaR_D} < \frac{CoVaR_U}{VaR_U}$
Wheat	0.6352	0.4535	0.9955
	[0.0000]	[0.0000]	[0.0000]
Corn	0.1629	0.3316	0.5539
	[0.0000]	[0.0000]	[0.0000]
Soybeans	0.749	0.5558	0.9988
	[0.0000]	[0.0000]	[0.0000]
Coffee	0.5876	0.3032	0.9206
	[0.0000]	[0.0000]	[0.0000]
Cocoa	0.0708	0.4156	0.5509
	[0.0000]	[0.0000]	[0.0000]
Cotton	0.1211	0.5133	0.6918
	[0.0000]	[0.0000]	[0.0000]
Lumber	0.0451	0.1031	0.3034
	[0.0000]	[0.0000]	[0.0000]
Live cattle	0.831	0.2204	0.9818
	[0.0000]	[0.0000]	[0.0000]

Note: Table provides the K-S statistic for equality of two cumulative distribution functions. P-values are given in square brackets. Column 1 tests for the equality of VaR and CoVaRs in the down market while Column 2 performs the same test in the up market. Column 3 reports the test results for the asymmetry of upside and downside risks.

5.3. Conditional diversification analysis

Table 7 reports the summary statistics of CDBs for various portfolio weights, based on the suggestions in Christoffersen et al. (2012) and Christoffersen and Simutin (2017) and at the 5% (Panel A) and 50% (Panel B) probability levels for the expected shortfall. The empirical evidence, based on the average values, suggest a reverse V-shaped pattern for all agricultural futures at the 5% and 50% levels, with the exception for live cattle futures offering virtually a same diversification benefits to investors at portfolio compositions of 50% and 80%. In addition, the averaged CDBs values are larger for all cases at the 5% level. The results reveal that the averaged CDBs for wheat, corn, coffee, and cotton are quite similar, whereas the CDBs for the remaining markets differ somewhat in magnitude. The benefits of diversification peak at portfolio compositions of 50% oil and 50% agricultural futures and then declines as the portfolio weights rise. Explicitly, we obtain the least and highest CDBs for portfolio weights of 5% and 50%, respectively, for all agricultural markets, with the exceptions for lumber and live cattle futures. In line with Hanif et al. (2023), lumber attains the highest CDBs for portfolio weights from 0.05 to 0.50, whereas live cattle futures contract acts as the derivative asset offering the highest diversification benefits for the remaining portfolio weights. Lumber (soybeans) futures evidently offers higher (lower) diversification benefits and risk reduction, given a relatively lesser (larger) standard deviation of 0.0246 (0.0602), for an equally weighted portfolio composition when both markets are in bearish circumstances. This result suggests that bivariate portfolios including lumber (soybeans) and oil futures are the most (least) attractive in diversifying the extreme risks of oil markets. However, this is true only for the lumber futures in the normal return quantiles, i.e. at the 50% expected shortfall.

Table 7: *Conditional diversification benefits*

		Wheat	Corn	Soybeans	Coffee	Cocoa	Cotton	Lumber	Live cattle
Panel A: Expected Shortfall at 5%									
Portfolio Weight									
0.05	**mean**	0.1833	0.1494	0.1242	0.162	0.1548	0.1561	**0.2026**	0.1113
	sd	[0.0598]	[0.0461]	[0.0417]	[0.0563]	[0.0468]	[0.0438]	[0.0587]	[0.0349]
0.2	**mean**	0.4599	0.4094	0.3639	0.43	0.4271	0.4215	**0.4947**	0.3494
	sd	[0.0841]	[0.0788]	[0.0798]	[0.0903]	[0.0800]	[0.0724]	[0.0732]	[0.0726]
0.5	**mean**	0.6091	0.5899	0.5667	0.602	0.6247	0.594	**0.6372**	0.5964
	sd	[0.0455]	[0.0497]	[0.0602]	[0.0583]	[0.0414]	[0.0382]	[0.0246]	[0.0528]
0.8	**mean**	0.4747	0.4931	0.5105	0.4903	0.5368	0.4824	0.4834	**0.5981**
	sd	[0.0874]	[0.0774]	[0.0791]	[0.0667]	[0.0560]	[0.0631]	[0.0713]	[0.0423]
0.95	**mean**	0.198	0.217	0.2421	0.2089	0.2438	0.204	0.194	**0.3185**
	sd	[0.0781]	[0.0748]	[0.0834]	[0.0610]	[0.0683]	[0.0597]	[0.0591]	[0.0680]
Panel B: Expected Shortfall at 50%									

Portfolio Weight									
0.05	**mean**	0.0445	0.0349	0.0283	0.0385	0.0363	0.0366	**0.0499**	0.025
	sd	[0.0173]	[0.0123]	[0.0107]	[0.0160]	[0.0127]	[0.0117]	[0.0179]	[0.0089]
0.20	**mean**	0.1514	0.1263	0.1067	0.1371	0.1347	0.1314	**0.1692**	0.1004
	sd	[0.0410]	[0.0343]	[0.0322]	[0.0426]	[0.0366]	[0.0324]	[0.0393]	[0.0288]
0.50	**mean**	0.2422	0.228	0.2127	0.2382	0.254	0.2302	**0.2632**	0.2332
	sd	[0.0319]	[0.0324]	[0.0373]	[0.0410]	[0.0283]	[0.0262]	[0.0186]	[0.0356]
0.80	**mean**	0.16	0.169	0.1793	0.1663	0.1928	0.1616	0.1629	**0.2335**
		[0.0471]	[0.0436]	[0.0464]	[0.0368]	[0.0349]	[0.0344]	[0.0387]	[0.0298]
0.95	**mean**	0.0495	0.0549	0.0631	0.0519	0.0629	0.0504	0.0475	**0.0884**
	sd	[0.0260]	[0.0249]	[0.0292]	[0.0196]	[0.0241]	[0.0189]	[0.0181]	[0.0262]

sd

Notes: We compute the conditional diversification benefit (CDB) for each bivariate portfolio including oil against agricultural futures contract considering expected shortfall values at the 5% (Panel A) and 50% (Panel B) probability levels. The table reports portfolio weights in first column and CDBs in columns 3–10. In addition, the time-average of the conditional diversification benefit and the standard deviation are given in the first and second row [in square bracket].

6. Conclusion

Crude oil and agricultural markets have been marked by high uncertainty after the financialization of commodities. Furthermore, the geopolitical conflicts and the economic and energy crises have contributed to the large swings of commodity prices. Oil is one of the most important input of agriculture sector. A surge in oil prices leads to an increase in agricultural prices. This linkage requires better understanding and measuring the spillover effects and the changes in the dependence structure between crude oil and major commodity futures. This paper aims to examine the dependence (average and extreme or tail) as well as risk spillovers between crude oil futures and eight major agricultural commodity futures wheat, corn, soybean coffee, cotton, lumber, cocoa, and live cattle. Furthermore, it investigates the potential diversification benefits using a variety of copula functions and Conditional Value at Risk (CoVaR) measure.

We obtain the following results. First, it show evidence of mean and volatility persistence in market returns, where oil market emerges as the most persistence and cocoa is the least. Furthermore, corn, cotton, soybeans, and wheat futures prices have symmetric tail dependence, whereas the coffee market has an average dependence on the oil market. Both cocoa and lumber markets show lower tail dependence, while the live cattle market exhibits concurrent lower and upper tail dependence. They co-move with oil market during bearish market circumstances but decouple when markets are bullish. Time-varying copula results reveal a statistically significant and time-variant dependence for cocoa and live cattle with oil market, confirming Wen et al. (2017). Besides, in line with Yahya et al. (2019), the level of tail dependence is not constant but time varying and intensifies during the major financial. Apart from other markets, the dependence level of coffee and live cattle markets switch sing from positive to negative for shortly periods, coinciding with the general strike in Venezuela, the Iraq war, and the onset of the pandemic, indicating the presence of safe-haven property for investors in oil market. The results show asymmetric and bidirectional risk spillovers from oil to agricultural markets and demonstrate that the effects of return spillover are more prominent during the COVID-19 pandemic, followed by the GCF and the oil price shock in 2014, with a larger impact during bearish market rather than bullish market conditions. The spillover effect from agricultural markets to oil market is larger than the other way around, indicating that oil market is more susceptible to volatility than agricultural markets during extreme conditions. We find that conditional (CoVaR) and unconditional VaR values exhibit similar upward and downward trends, with minor differences in magnitude, and unconditional downside/upside VaR values mostly and systematically larger than CoVaR values, reinforcing the findings existing literature such as Ji et al. (2018) and Meng et al. (2020). The wheat futures contract, followed by lumber and corn futures, respectively, appears to be the most dominating and vulnerable asset to oil price shocks, while the live cattle contract emerges as the least sensitive. The empirical evidence from the conditional diversification benefits suggest a reverse V-shaped pattern for all agricultural futures at the 5% and 50% expected shortfall levels. The highest benefits are available in equally weighted bivariate portfolios for all cases. Finally, yet importantly, lumber (soybeans) futures evidently offer higher (lower) diversification benefits and risk reduction when both markets are in bearish circumstance.

Our results hold multifaceted implications for agricultural investors and policymakers. From investors' point of view, the asymmetric dependence between oil and agricultural futures markets during extreme market conditions calls for dynamic portfolio management and asset allocation decisions to achieve better diversification benefits. In addition, the presence of dependence linkage of agricultural commodities drives the need for a better understanding of its hedging effects towards uncertainty in oil markets and allows for the precise pricing of futures contracts over various market circumstances. On the other hand, our results will help policy makers to design appropriate policies to minimize the effects of spillover shocks as well as reduce vulnerabilities of the agricultural markets to oil shocks and vice versa. First of all, understanding the major dynamics behind downside and upside risk propagations will enable policymakers to establish effective policies and maintain stability in closely related and mutually dependent markets. Policymakers should first identify whether oil-related risks to agricultural commodity markets are caused by nonmarket or market-specific variables such as supply, demand, or others, and then develop appropriate policies. It is essential to note that the upward and downward dependency observed between the two markets cannot be avoided (Shahzad et al., 2018), given the importance of oil as a global production cost and some agricultural items as a main input for alternative fuels to oil. Therefore, actions to mitigate the potential consequences of events that might disrupt the supplydemand balance of the oil market, which is highly sensitive to geopolitical and economic events, on the country's economy, agricultural production, and investors should be conducted. Excessive speculation on agricultural prices to hedge against the negative consequences of global or regional market variations may result in strong demand and hence excessive volatility in both spot and futures prices. It is proposed that futures markets be more effectively regulated, agricultural production be increased through subsidies, and non-oil energy sources be developed, or productions be supported through legislation against upside risks; thus, it is possible to reduce the burden on consumers caused by rising inflation due to excessive price fluctuations. On the other hand, for countries that rely heavily on commodity export income, it should be noted that decreases in agricultural commodity prices caused by the oil market may result in a decrease in agricultural production (a fall in producer income), an increase in poverty, and thus a decline in economic growth, as well as long-term social unrest. Investigating the impacts of different uncertainty factors on the risk spillover and dependence linkage between agricultural and oil futures markets over various investment horizons remains on the research agenda.

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Walid Mensi: Conceptualization, Supervision. **Mobeen Ur Rehman:** Methodology, Data Curation, Software, Formal analysis. **Remzi Gök,**: Writing - original draft; administration. **Eray Gemici:** Formal analysis, Writing - original draft. **Xuan Vinh Vo**: Supervision, resources, administration

Highlights

- We examine dependence structure and risk spillovers between crude oil and eight major agricultural futures markets.
- Conditional diversification benefits, copula functions and Conditional Value at Risk (CoVaR) measure are used.
- Results show significant crisis-sensitive and temporal dependence between oil and agricultural markets.
- Moreover, crude oil shows a symmetric tail dependence with both wheat, corn, soybeans, and cotton futures
- An equally weighted portfolio offers the highest diversification benefits at a 5% expected shortfall.